Evaluation of visual parameters to control a visual ERP-BCI under single-trial classification

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Abstract. A brain-computer interface (BCIs) based on event-related potentials (ERPs) is a technology that provides a communication channel between a device and a user through their brain activity. These systems could be used to assist and facilitate decision making in applications such as an air traffic controller (ATC). Thus, this work attempts to be an approximation to determine whether it is possible to detect the stimulus through a single presentation of a stimulus (single-trial classification) and furthermore, to evaluate the effects of the type of stimulus to be detected, or not knowing the position of the stimulus appearance in an ERP-BCI. This experiment has involved six participants in four experimental conditions. Two conditions varied only in the type of stimulus used, faces (a type of stimulus that has shown high performance in previous ERP-BCI proposals) versus radar planes; and two conditions varied in the prior knowledge of where the stimulus would appear on the screen (knowing vs. not knowing). The results suggest that the use of single-trial classification could be adequate to correctly detect the desired stimulus using and ERP-BCI. In addition, the results reveal no significant effect on either of the two factors. Therefore, it seems that radar planes may be as suitable stimuli as faces and that not knowing the location of the target stimulus is not a significant problem, at least in a standard BCI scenario without distracting stimuli. Therefore, future studies should consider these findings for the design of an ATC using an ERP-BCI for stimulus detection.

Keywords: Brain-Computer Interface (BCI), Event-Related Potential (ERP), Single-Trial Classification, Air Traffic Controller (ATC).

1 Introduction

Brain-computer interfaces (BCIs) use brain activity to create a communication pathway between a device and a user [1]. The most common method to measure brain activity in a BCI is electroencephalography (EEG) [2]. EEG has several advantages such as its low cost, non-invasive nature, and good temporal resolution [3]. BCIs have been employed in several areas, including clinical and recreational applications [4]. Recent research suggests that BCIs could also be useful in decision-making and monitoring user states during surveillance tasks in situational awareness contexts [5, 6]. Situational awareness refers to the comprehension of environmental conditions and events, considering their temporal and spatial context, as well as predicting their potential future states. A hierarchical framework, proposed by [7], identifies three levels to approach SA: (i) perception of current situation elements, (ii) comprehension of the current situation, and (iii) prediction of future situations.

Air traffic control (ATC) is a scenario where a trained operator guides planes on the ground and through a specific area of regulated airspace. The primary objectives of ATC are to prevent collisions, organize air traffic flow, and provide pilots with relevant information and support. Therefore, ATC could be a suitable scenario for the use of brain-computer interfaces (BCIs) to aid decision-making, where a user needs to be aware of different cues and respond accordingly [8–10]. This paper focuses on the applications of BCIs for ATC, with the aim of enhancing the safety and precision of the controlled system. Two types of BCI systems can be distinguished to achieve these objectives: passive and active. A passive BCI aims to recognize the user's state during task execution, such as their level of tiredness or mental workload [10]. This information could be valuable for the system to detect potential errors in detecting critical cues for preventing incidents [11, 12]. On the other hand, an active BCI would assist with decision-making, such as detecting the appearance of new relevant elements on the map. To our knowledge, there is no previous work that has employed an active BCI for detecting new elements in the ATC scenario. Hence, this study focuses on active BCIs and the first level of the situational awareness framework, i.e., perceiving elements in the current situation. This involves detecting the appearance of new key elements—such as new planes on the map—using the user's EEG signal to control the system.

ATC operators are required to attend to planes as visual stimuli on a virtual map, so this study uses visual event-related potentials (ERPs) recorded through EEG as the input signal for detection. Visual ERPs refer to potential changes in brain activity that occur in response to the presentation of visual stimuli. ERPs are influenced by factors such as the type [13], size [14, 15], and luminosity [16] of the stimuli. When designing a visual ERP-BCI for an ATC scenario, it's important to consider these factors based on previous research. There are some key differences between visual ERP-BCI applications like wheelchair [17] or virtual keyboard [18] control and ATC. For instance, the number of times the target stimulus is presented (only one) and the location of its appearance (unknown) are especially relevant in the case of an ATC application. In most visual ERP-BCI applications, the target stimuli are displayed multiple times to increase the likelihood of accurate selection. However, in applications such as ATC where alert messages are presented, it is crucial that the target stimulus can be recognized just after one presentation. This requires the visual ERP-BCI to operate with single-trial classification, where the detection of a target stimulus is identified from a single presentation of the stimulus. However, this presents a challenge as ERP-BCIs typically require multiple stimulus presentations to effectively distinguish the relevant components of the EEG signal from the noise, such as muscle artifacts. The noise level decreases as more presentations are made, allowing better observation of ERP components associated with the presentation of a target stimulus. However, previous ERP-BCI proposals that focus on using single-trial classification have shown acceptable performance (~80% accuracy [19–21]). However, these previous works employed a different scenario than the one used in an ATC, i.e., they did not address the characteristics that could constrain the performance of an ATC, such as the type of visual stimuli to be attended, the use of a stimulus-rich map as background, moving planes, or small target stimuli like the planes to be detected. Therefore, exploring the use of single-trial classification under some specific characteristics presented in an ATC scenario could be worthwhile. In visual ERP-BCIs, the best performing stimuli to date are the red faces on a white background [22], and they are presented in a specific location that the user knows beforehand; however, in an ATC, the used stimulus are planes that appear in an unknown location. Therefore, it would be interesting to assess whether the type of stimulus to be attended and not knowing the position of stimulus appearance affects performance.

The objective of this study was to explore the use of single-trial classification and the impact of two visual factors on the accuracy of a visual ERP-BCI system in detecting new planes in a situational awareness scenario by an ATC. The utilization of an active BCI to aid an ATC is a unique approach; hence, two experiments were carried out to explore this approach. The initial experiment aimed to test the single-trial classification and BCI single-character paradigm (SCP) [23] to analyze the effects of different variables. It involved the presentation of two types of stimuli (faces and radar planes) and determining the impact of knowing or not knowing the location where the target stimulus would appear.

2 Method

2.1 Participants

The study has involved six participants (22.6 ± 1.52 years old, one woman, named P01-P06). Only P01 and P02 had previous experience in the control of an ERP-BCI. All subjects gave their written informed consent on the anonymous use of their EEG data. They declared having normal or corrected-to-normal vision. The study was approved by the Ethics Committee of the University of Malaga and met the ethical standards of the Declaration of Helsinki.

2.2 Data acquisition and signal processing

Signals were recorded through eight active electrodes, namely Fz, Cz, Pz, Oz, P3, P4, PO7, and PO8 (10/10 international system). A reference electrode was placed on the left mastoid, and a ground electrode was placed at AFz. An acti-CHamp amplifier (Brain Products GmbH, Gilching, Germany) was used, with a sample rate of 250 Hz, a band-pass filter of 0.1-30 Hz, a notch filter of 50 Hz, and an epoch length of 800 ms. The data were collected by BCI2000 [24]. When offline tasks were over, the weights of a classifier were calculated from the data of the condition tested through a stepwise linear discriminant analysis (SWLDA), using the P300Classifier, a BCI2000 tool. These weights were later used to carry out online tasks and to offer feedback to participants.

An HP Envy 15-j100 laptop was used (2.20 GHz, 16 GB, Windows 10), but the display was an Acer P224W screen of 46.47 × 31.08 cm (16:10 ratio), connected through HDMI, at a resolution of 1680 × 1050 pixels. The refresh rate of the screen was 60.014 Hz.

2.3 Experimental conditions

This experiment aimed to investigate the impact of the type of stimulus used and whether the participant was aware of where the stimulus would appear on the performance of a visual ERP-BCI. The experiment used the BCI2000 software [24] and employed the SCP [23] with single-trial classification. The SCP involves presenting each stimulus sequentially at a different position on the display, with nine possible locations arranged in a 3x3 matrix. The stimuli used in the experiment varied based on the experimental condition, but they all measured 3.4 × 3.4 cm and were displayed on a black background. The user's distance from the screen was approximately 60 cm. The goal was to validate the use of an active BCI for detecting a stimulus presented only once in a specific position on the screen, which is similar to the case of plane detection for an ATC. The following experimental conditions were used:

C1-faces. The stimuli used were red celebrity faces with a white square background, a type of stimuli that has been suggested by recent work as one of the most appropriate to obtain high accuracy in the control of a visual ERP-BCI [22]. Both target and non-target stimuli were presented, and the user knew in advance the exact position of appearance of the target stimulus.

C2-planes. It was the same as C1-faces—the presence of target and non-target stimuli and the user knew the specific location of the target stimulus—but employed symbols similar to those used for planes on radars.

C3-known. The stimuli were also radar planes and the user knew in advance the exact position of the target stimulus. However, the non-target stimuli were not presented, i.e., only the target stimulus to be attended by the user appeared on the screen.

C4-unknown. It was similar to C3-known as it also employed radar plans, and non-target stimuli were not presented; however, in this condition, the user did not know in advance where the target stimulus would appear.

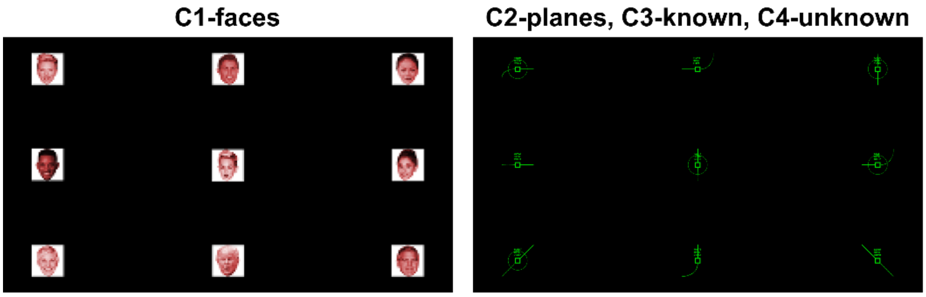

Fig. 1. Stimuli and locations used to present them on the screen. The C1-faces condition used celebrity faces, while the C2-planes, C3-known, and C4-unknown conditions used stimuli that simulated those used on flight radar. Images of celebrity faces have been pixelated for copyright reasons. The celebrity faces were (from left to right and from top to bottom): Scarlett Johansson, Cristiano Ronaldo, Rihanna, Will Smith, Miley Cyrus, Ariana Grande, Ellen DeGeneres, Donald Trump, and George Clooney.

The present study has had a progressive approach in order to evaluate relevant factors in the use of an ERP-BCI for the detection of new elements in an ATC scenario. For this purpose, different conditions have been evaluated until reaching C4-unknown, in which the stimuli were radar planes appearing in an unknown position of the interface, as it would happen in an ATC scenario. Thanks to this progressive approach, in addition to the use of single-trial classification, two factors have been evaluated during the experiment across the different conditions. Specifically, the aim of these conditions was to study the effect of two factors on system performance when detecting the presence of specific target stimuli in the interface based on the user's EEG signal. On the one hand, comparison between C1-faces and C2-planes allowed evaluating the effect of the type of stimulus. On the other hand, comparison between C3-known and C4-unknown allowed evaluating the effect of knowing in advance the exact location of appearance of the target stimulus.

2.4 Procedure

The participant arrived at the laboratory and received an explanation of the experimental procedure. They provided informed consent, the EEG electrodes and cap were placed, and the tasks could begin. The testing involved a design where each participant completed all conditions, which included a calibration task to adjust the system and an online task where the system aimed to detect specific stimuli. During the online task, the user received feedback on their performance based on specific parameters (i.e., the weights for the P300Classifier) already calculated after the calibration task. The terms used to detail the procedure of the experiments included the following. A run is the process to detect a single target stimulus. To complete a run, all the stimuli that compose the interface must be presented. A block is the interval from when the interface is started until it stops automatically; it is composed of the different runs made by the user.

The experiment was divided into two consecutive sessions: a first session with conditions C1-faces and C2-planes, and a second session with conditions C3-known and C4-unknown. The order of the conditions of each session was counterbalanced among the subjects. The approximate duration of the experiment was 80 minutes from the time the participant arrived at the laboratory until the end of the tasks. The four conditions used in this experiment had similar timing. Before the start of each block there was a waiting time of 1920 ms, after which the different runs began. Moreover, at the beginning of each run (except for C4-unknown), a message was presented in Spanish ("Atiende a:" [Focus on:]) for 960 ms, after which the stimulus to be attended to was presented for another 960 ms. For C4-unknown, this information was replaced by a black background for 1920 ms. Before the first stimulus of the run was presented, all conditions included a pause time of 1920 ms. The stimulus duration was 384 ms, and the inter-stimulus interval (ISI) was 96 ms, resulting in a stimulus onset asynchrony (SOA) of 480 ms. Likewise, in the online task in all conditions, a message was presented at the end of each run ("Resultado:" [Result:]) for 960 ms, after which the stimulus selected by the system was presented for 960 ms. The attention and result messages were accompanied by an auditory cue to facilitate the user's attention to the task. For both the calibration and online tasks, a pause time of 1920 ms was added. The specific procedure for the C1-faces and C2-planes conditions was identical, as was the specific procedure for C3-known and C4-unknown, so the particularities of each condition in this experiment are detailed below.

C1-faces and C2-planes. The calibration task consisted of three blocks of six runs of 55 s each (Figure 2). In each block, the following stimuli were selected from left to right: for the first block, the three stimuli in rows 1 and 2; for the second block, the stimuli in rows 2 and 3; and for the third block, the stimuli in rows 1 and 3. Each block of the calibration task had a duration of 55 s. The online task consisted of presenting as target stimuli all stimuli of the interface in row-major order, that is, nine runs in one block, which had a duration of 111 s. (E01 and E02 performed 18 runs instead of 9).

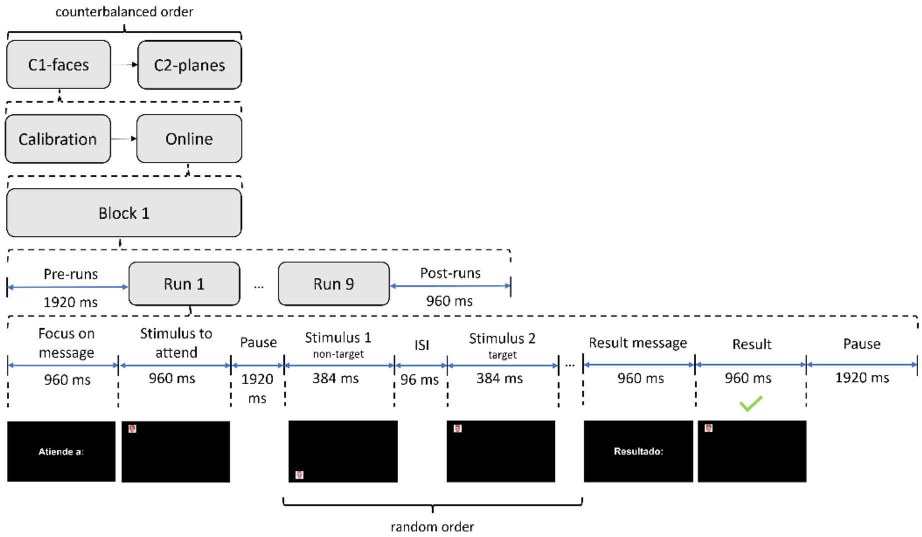

Fig. 2. Procedure and timing used in conditions C1-faces and C2-planes. Specifically, the figure shows the execution of the first run of the C1-faces condition during the online task. ISI stands for inter-stimulus interval.

C3-known and C4-unknown. The calibration task consisted of 16 blocks of one run, resulting in a duration of 11 s per block (Figure 3). The online task used five blocks of one selection, with a duration of 14 s per block (E01 and E02 performed 10 blocks of one selection). For both tasks, the target stimulus order to be attended to was randomly selected with replacement.

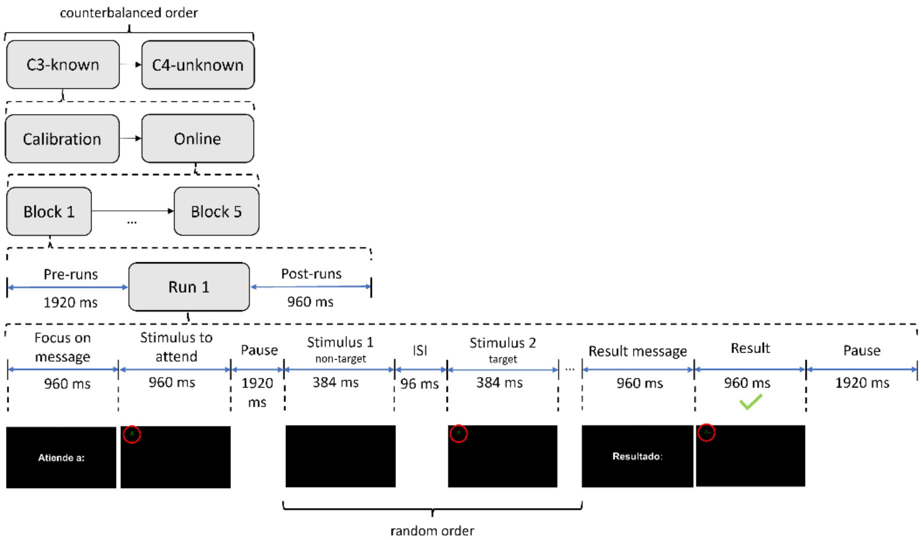

Fig. 3. The procedure and timing used in conditions C3-known and C4-unknown. Specifically, the figure shows the execution of the first selection of the C3-known condition during the online task. Due to the small size of the stimulus in the figure, compared with when it was presented on the screen during the experiment, the stimulus has been marked with a red circle here. ISI stands for inter-stimulus interval.

2.5 Evaluation

In all conditions, the classifier had to select a target stimulus from nine possible stimuli (including E1-know, C4-unknown, in which the non-target stimuli were invisible to the user). The accuracy (%) corresponds to the percentage of correct selections divided by the total number of selections made. The accuracy was calculated for the online task of each condition. The Wilcoxon signed-rank test, a non-parametric test for the comparison of two related samples, was used to compare between the conditions. All these analyses were carried out using SPSS software [25].

3 Results and discussion

In this experiment, in addition to single-trial classification, two factors were evaluated: (i) the stimulus type (faces versus radar planes), using visible non-targets; and (ii) the knowledge of the location of the stimulus to attend to before it appears (known versus unknown), using the radar plane stimulus type and invisible non-target stimuli (Table 1). In general, the results obtained (between 60% and 80% accuracy depending on the condition) are below those usually employed by other ERP-BCI applications that are not based on the single-trial classification approach (which can easily exceed 90% accuracy in applications such as virtual keyboards [26]). These results were expected since indeed the reason for using several presentations of the target stimulus is to increase the performance. Therefore, the results obtained highlight the challenge of detecting the target stimulus after a single presentation of it. The following results for the two visual factors studied—the type of stimulus and the knowledge of the place of appearance of the target stimulus—are detailed next. First, the C1-faces and C2-planes conditions were compared (64.81 ± 34.73 %, and 69.45 ± 30.98 %, respectively). The Wilcoxon signed-rank test showed that there was no significant difference between the conditions (Z = 0.406; p = 0.684). Therefore, it seems that type of stimulus does not have a significant impact on performance. Second, to test the effect of prior knowledge of the stimulus location, the C3-known and C4-unknown accuracies were compared (75 ± 25.1 %, and 76.67 ± 15.06 %, respectively). The Wilcoxon signed-rank test showed that knowing the location of the stimulus beforehand did not affect accuracy (Z = 0.378; p = 0.705). Therefore, these results showed that knowing where to attend to the incoming target did not affect performance.

Table 1. Mean ± standard deviation accuracy (%) for each user in the online task.

User	C1-faces	C2-planes	C3-known	C4-unknown
P01	100	88.89	90	80

P02	100	94.44	100	80
P03	88.89	88.89	60	80
P04	33.33	66.67	100	100
P05	33.33	66.67	60	60
P06	33.33	11.11	40	60
Mean	64.81 ± 34.72	69.45 ± 30.98	75 ± 25.1	76.67 ± 15.06

There are two important aspects related to performance that can be discussed: (i) the impact of the type of stimulus used and (ii) the effect of the size of the appearance surface of the target stimulus. Regarding the type of stimulus used, there was no significant effect on the performance of the system when using an ERP-BCI under the SCP (faces vs. radar planes), which is consistent with previous research that did not find that face stimuli offered significantly better performance than alternative stimuli [33,34]. Therefore, using radar planes as visual stimuli could be appropriate in the use of an ATC system managed through an ERP-BCI. On the other hand, not knowing the exact place of appearance of the target stimulus has not led to a decrease in the performance of the ERP-BCI when detecting these stimuli. This evidence could indicate that in applications such as an ATC it should not be, initially, a problem to lack knowledge of the place of appearance of the target stimulus. However, it should be considered that in the current experiment the interface where the stimulus appeared had no distracting elements, which could be interesting to study in future studies and would be closer to a real use of these applications. Some examples of factors that could make the task more difficult in a real ATC could be the presence of multiple moving planes on the screen, a smaller size of the target stimuli or a map on the background with additional information.

The accuracy results have been very heterogeneous, from participants who have even obtained 100% to others with a lower accuracy than 50%. It is worth emphasizing that most of the participants in the study had no previous experience in the control of an ERP-BCI. Indeed, users P01 and P02, the only participants with previous experience in the use of ERP-BCI systems, were the only ones who presented an accuracy of at least 80% in all the conditions, even reaching 100% in C1-faces. Therefore, we cannot exclude the possibility that through extended training in the use of the system, the performance may be better, which would allow the use of single-trial classification to accurately detect the target stimuli.

4 Conclusions

The present work has been a preliminary study on the use of an ERP-BCI under the single-trial classification approach and its future application to an air traffic controller. Specifically, it has been shown that (i) it is possible to achieve an adequate performance under the single-trial classification approach, (ii) radar plane stimuli may be suitable for use as visual stimuli in an ERP-BCI visual, and (iii) not knowing the location of occurrence may not have a significant effect on their performance. As we said, these results can be applied to the use of an ERP-BCI in the control of an ATC. However, the accuracy shown confirms that the use single-trial classification is a challenge in the BCI domain and the user experience could be an important factor. As the combination of an ATC and a BCI is a relatively novel area, there is considerable scope for future proposals. For instance, the results are promising to be implemented in a real ATC scenario; it would be interesting to test these findings in a real ATC, where, for example, there are other distractor stimuli or the size of the area in which the target stimulus could appear is specifically studied. Also, future studies should focus on improving the performance of the visual ERP-BCI systems by considering what has been previously studied in other types of BCI devices, such as spellers which are the most studied ERP-BCI applications [26]. Possible areas of improvement include those related to human factors [27] and different signal processing and classification techniques [28]. While BCI systems have been used previously in the field of ATC to assess the cognitive state of users (assessment of mental workload [11] or the presence of microsleep states [12]), it would be interesting to use them with the dual purpose of measuring the cognitive state of the user (passive BCIs) and supporting the correct perception of stimuli at the interface (active BCIs). Overall, the use of an ERP-BCI for stimulus detection in an ATC is an interesting area that could be further explored, as the present work has shown that the presentation of a radar plane under a black background produces an ERP waveform that can be discriminated by a BCI system, even when the location of the stimulus is previously unknown to the user.

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